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Digital Machines, Space, and Time: Towards a Behavioral Perspective of Flexible Manufacturing

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Recently, the diffusion of digital machines has further enhanced firms' manufacturing flexibility, but also opened questions on potential challenges and implications in the production process. To respond to these timely issues, this study adopts a behavioral perspective and comparatively explores how four different types of digital machines—characterized by increasing degrees of manufacturing flexibility—affect the perception and use of space and time for routines within the production plant. To this end, 45 digital manufacturing machines, sampled across 14 firms in the British and Italian motorsport industry, were qualitatively observed and compared. A model emerges where four key mechanisms reshape (1) the interactive space around the machine, (2) the innovation activities performed in the machine space, (3) the time within activities involving the machine, and (4) the time perception. Such mechanisms mediate the relationship between manufacturing flexibility and firm performance. Further, data show how increasing digitalization in the manufacturing process enhances the establishment of new routines as flexible machines get introduced in the production. Finally, theoretical and practical implications related to fostering a behavioral perspective in innovation and operations management studies are discussed.

Practitioner Points

- Despite their ability to provide further degrees of manufacturing flexibility, digital technologies are far from being "plug-and-play" solutions.
- To fully exploit their potential, managers need to develop a better understanding of the behavioral patterns related to their adoption in the production process, so far overlooked both in theory and practice.
- The adoption of digital technologies influences the reshaping and development of novel routines related to "space" and "time" on the production floor.
- Managers are advised to engage with specific training and assessments to help employees understand and adapt to the not-so-evident changes that the adoption of digital machines entail.

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Introduction

The paradigmatic shift from traditional to digital manufacturing—recently embodied by the diffusion of 3D printing—has enhanced firms' manufacturing flexibility (Eyers, Potter, Gosling, and Naim, 2018); changed their innovation and business models (D'Aveni, 2015); shrunk and reconfigured their supply chains (Holmström and Chaudhuri, 2017; Rogers, Baricz, and Pawar, 2016); and, overall, altered the global economy (Khorram Niaki and Nonino, 2017). The significant influence of digital manufacturing on the business world is a central component of the so-called "Fourth Industrial Revolution" (Andreson, 2012; Ardito, Petruzzelli, Panniello, and Garavelli, 2019; Hopkinson, Hague, and Dickens, 2006; Rifkin, 2008).[1] Research on flexible manufacturing systems and advanced manufacturing technologies has shed light on several phenomena related to innovation, organizational, operational, and economic performance, as well as their overall linkage to operations strategy (Cagliano and Spina, 2000; Swink and Nair, 2007). Yet, the diffusion of additive manufacturing (AM) technologies is one of the last steps in a long path of digital machines which, in several cases, are designed to provide further degrees of manufacturing flexibility (Eyers et al., 2018), and are increasingly attracting scholars' attention, thus creating a sort of "hype" regarding the potential advantages of AM technologies (D'Aveni, 2015; de Jong and de Bruijn, 2013).[2]

However, while the advantages of such technologies are undeniable, an acritical approach, which largely (or exclusively) focuses on benefits, presents worrying limitations. In fact, in the academic and industry literature, the complexities and potential pitfalls associated with the implementation of such technologies remain unclear. For instance, digital manufacturing machines are often incorrectly considered to be "plug-and-play" solutions, and managers tend to underestimate the complex factors influencing the effective implementation of digital manufacturing—see among others Adidas' recent struggles to scale-up its 3D-printed insoles to mass production (Tepper, 2017). Thus, new perspectives are needed to shed light on non-trivial aspects related to the timely challenges that today's digital technologies face. Interesting contributions come from the innovation management literature, where scholars have investigated how innovative technologies—including digital ones—can have critical effects on innovation outputs; the development of organizational capabilities; and ultimately, firm performance (Colarelli O'Connor, 2008; Hopp, Antons, Kaminski, and Salge, 2018; Michael and Palandjian,

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[1]For instance, 3D printers have supported the collaboration of engineers and medical experts to enable the generation of new solutions in the health industry, such as the production of body parts and customized aids. In the fashion industry, the collaborations of manufacturing experts and designers developed a change in couture conceptualization (Lupton, 2015; Su and Pirani, 2013). Finally, scholars affirm that additive manufacturing will force firms to change their approaches to sustainability (Despeisse et al., 2017; Holmström, Liotta, and Chaudhuri, 2018).

[2]Despite the current interest in the diffusion of 3D printers, other digital machines have preceded the introduction of AM technologies and are still in great use within production companies (see for example digital milling machines and digital production lines). Our study will compare four kinds of such digital machines, exploring how increasing flexibility in their manufacturing scope affects individuals' routines related to the use and perception of space and time.

2004; Rindfleisch, O'Hern, and Sachdev, 2017; Svahn, Mathiasse, and Lindgren, 2017).

Scholars have been developing frameworks at the intersection of several bodies of literature to understand and implement digital technologies in manufacturing (e.g., Holweg, 2015; Mellor, Hao, and Zhang, 2014; Rayna and Striukova, 2016; Su and Pirani, 2013; Weller, Kleer, and Piller, 2015). Among those, the operations management literature has been one of the main literatures to investigate how digital technologies increase manufacturing flexibility on the production floor (Mishra, Pundir, and Ganapathy, 2018; Oke, 2005). However, such literature has primarily adopted an engineering-based approach, where key constituting elements of *space* (defined as the *locus* of where the organization "happens") and *time* (defined as the production and activity scheduling) are often conceptualized and assessed simply as objective measurable dimensions (see Neely, Gregory, and Platts, 2005, for a discussion on performance measures in manufacturing). This specific view overlooks the more subjective, less directly observable components of space and time. These subjective dimensions have paramount implications for firms, including understanding the critical interaction between humans and machines, which significantly influences firm performance, and moving firms toward a more comprehensive understanding of the "human factor" (Gino and Pisano, 2008). In fact, flexible manufacturing machines may affect the activities executed by individuals working on the production floor, due to changes not only in the production workflow and layout, but also in the prioritization of different activities and their execution time (Neely et al., 2005). Accordingly, flexible manufacturing machines foster the development of new patterns of actions (Becker, Lazaric, Nelson, and Winter, 2005).

Technological changes often demand an organization to make complex and challenging adaptations to their routines (Feldman and Pentland, 2003)—that is, the recurring patterns of activities tightly intertwined with individuals' experimental wisdom, and derived from learning processes and reinforcing behaviors (Nelson and Winter, 1982). Building on the influence of technological changes, this study suggests that the introduction of digital manufacturing machines aimed at increasing flexibility in the organizations' production can have a disruptive effect on individuals' routines. In other words, the introduction of new manufacturing technologies may lead individuals not only to change the ways they interact with the technology and with third parties (Gavetti, 2005; Lorenzoni and Lipparini, 1999; Teece, 2007), but also affect the type of routines they develop in production and process-specific contexts (Aggarwal, Posen, and Workiewicz, 2017; Becker et al., 2005; Feldman and Pentland, 2003). Changes in the degree of manufacturing flexibility enabled by the introduction of new technologies (such as digital machines) constitute the micro-foundation of the changes in organizational routines (Felin, Foss, Heimeriks, and Madsen, 2012). Hence, the evident impact of flexible manufacturing machines on routines and more intangible aspects, such as cognition—the mental process by which external or internal input is transformed, reduced, elaborated, stored, recovered, and used (Neisser, 1967)—suggest the need for a new theoretical lens in the operations management literature. Such a perspective should provide concepts and approaches that explore less measurable elements of the production process, which lend themselves to more subjective interpretations (Bendoly, Donohue, Schultz, 2006; Fahimnia, Pournader, Siemsen, Bendoly, and Wang, 2019). A perspective of this kind can explore how the innovation processes interact with new product creation and organizational capabilities (Colarelli O'Connor, 2008; Hopp et al., 2018; Michael and Palandjian, 2004; Slater, Mohr, and Sengupta, 2014).

This article posits that to understand the impact of digital technologies on individuals' manufacturing routines, the adoption of a *behavioral perspective* is necessary (Argote and Greve, 2007; Cyert and March, 1963; Gavetti, Greve, Levinthal, and Ocasio, 2012; Kavusan and Frankort, 2019). Thus, focusing on organizational routines and cognition in the contexts of the adoption of digital manufacturing can help elucidate why organizations are still facing challenges in effectively integrating flexible technologies, and in turn, often failing to fulfill the expectations of superior business performance and a sustainable competitive advantage. Using the perspective offered by the Behavioral Theory of the Firm (Cyert and March, 1963), this study attempts to open the "black box" of innovation by observing a wide set of digital machines, and investigating how their varying levels of manufacturing flexibility affects organizational routines. In doing so, it focuses on space and time, as well as the level of digitalization of the production process—that is, the use of digital information to fundamentally revisit intra and interorganizational decision-making, processes, and architectures, as defined by Holmström, Holweg, Lawson, Pil, and Wagner (2019). Thus, this study addresses the question: *How do increasingly flexible digital manufacturing machines influence routines related to space and time in the production process?*

The main focus of the article is on the "less measurable" nature of technological adoption, which includes the individuals' perceptions of space and time—thus carefully inquiring into the cognitive implications, which are well suited to exploring individual behaviors. Empirically, qualitative data were collected from the British and Italian motorsport industries, which develop racing technologies adopted in Formula One, Formula E, Le Mans Prototypes, Gran Turismo, and sport car production; the data were then analyzed. The motorsport industry is an innovation-driven setting where firms have extensively adopted a broad range of digital manufacturing machines, including AM.

Our study advances an overarching conceptual framework that connects a firm's adoption of digital machines to manufacturing flexibility. The conceptual framework unpacks four key mechanisms that redefine the "space–machine" and "time–machine" routines: reshaping the (1) interactive space around the machine, (2) innovation activities performed in the machine space, (3) time within activities involving the machine, and (4) time perception. In the conceptual framework, digitalization was considered not only in its traditional role as a potential enabler of manufacturing flexibility (Caggiano, Caiazzo, and Teti, 2015; Culot, Nassimbeni, Orzes, and Sartor, 2020), but more importantly, how it serves as a moderator of the relationship between such flexibility and routines. Specifically, our claim is that the increasingly intangible aspects of digital technologies—for example, bit-string assets such as digital files, digital blueprints, and software; digital communication protocols; and digital decision support systems—further enhance the emergence of new routines, which mediate the relationship between technological adoption and firm performance. Finally, this article contributes to a recent conversation in the literature on the Behavioral Theory of the Firm (Argote and Greve, 2007; Gavetti et al., 2012), and discusses its strategic implications for operations (Gino and Pisano, 2008) while also broadening to the innovation management and operations management literatures. Incorporating these literatures helps to shed light on innovation dynamics in manufacturing, where current technological disruptions are underpinning non-trivial phenomena at the intersection between digital transformation and production technologies.

Theoretical Background

The Role of Manufacturing Flexibility in Production Processes

The role of manufacturing flexibility in production processes has heavily attracted innovation and operations scholars' attention throughout the last 30 years (Browne, Dubois, Rathmill, Sethi, and Stecke, 1984; Buzacott and Yao, 1986; Cagliano and Spina, 2000; Davenport, 1993; Macduffie, 1995; Myint and Tabucanon, 1994; Slack, 1987; Van de Ven, 1986). Improving manufacturing flexibility is traditionally considered one of the main competitive levers for firms operating in increasingly uncertain environments and competitive markets. Such flexibility allows managers to rapidly change production outputs and develop new products more efficiently, as well as effectively respond to competitive challenges (De Toni and Tonchia, 1998; Oke, 2005). To date, research on the evolution of manufacturing technologies has primarily focused on flexible manufacturing systems and advanced manufacturing technologies (Kotha and Swamidass, 2000; Swink and Nair, 2007). Such literature has traditionally identified and analyzed compelling implications for supply chains (Slack, 1987), operations strategy (Gerwin, 1993; Upton, 1994)—such as opportunities for mass customization (da Silveira, Borenstein, and Fogliatto, 2001)—and wider influence on performance at different levels (Gupta and Somers, 2009; Swamidass and Newell, 1987).

Underlining the positive dimensions of manufacturing flexibility, Jain, Jain, Chan, and Singh (2013) suggested that flexibility represents an opportunity to adapt to market demands and it supports firms in gaining a competitive edge by enhancing customer engagement, and putting competitors under pressure. Yet, flexibility is characterized as multidimensional and complex (Eyers et al., 2018; Jain et al., 2013; Oke, 2005) and scholars agree that a firm's manufacturing flexibility is dependent on a number of different variables (Boyle and Scherrer-Rathje, 2009; Chang, Lin, Chen, and Huang, 2005; Mishra, 2016; Mishra et al., 2018; Swamidass, 2002). New digital technologies have the potential to increase the flexibility of production machines and processes (Caggiano et al., 2015; Culot et al., 2020); however, they are not the only enabling factor of manufacturing flexibility. Oke (2005, p. 991) provides a framework for achieving system flexibility where "information and process technologies" are "generic enablers" and they do not always lead to flexibility improvement. In fact, Oke (2005) shows that a mix of factors (rather than a single one) may be the most appropriate way to enable superior flexibility.

Accordingly, in our study, digital technologies (and their integration with manufacturing machines) are considered independent and do not always correlate with manufacturing flexibility. In fact, while several traditional tools or machines that are not embedding digital technologies (e.g., drills, hammers, lathes, non-digital milling machines) can still offer high manufacturing flexibility, several digital machines, and modern production lines, can be dedicated to one single component, thus exhibiting low or no manufacturing flexibility.

The Digitalization of the Manufacturing Process, Space, and Time

When introduced in a production plant, flexible manufacturing machines occupy an existing or a new organizational *space*—that is, the *locus* where the organization "happens" and where external and internal agents often interact to engage with the scope of the organization itself (Taylor and Spicer, 2007). The organizational space is usually theorized as an enabler of the firm's activities and innovation processes, in the sense that its configuration might broaden or restrict firms' scope and activities (Allen and Cohen, 1969; Fayard and Weeks, 2007, 2011). Literature suggests that increasingly flexible technologies tend to initiate significant changes not only in the type of outputs (e.g., new products and solutions), but also in the users' perception and use of space—for example by triggering a visible reorganization of the physical space where operations take place (Bolwijn and Kumpe, 1990; Clegg and Kornberger, 2006). The changes in the organizational routines related to new spatial arrangements present an interesting but nonetheless complex matter that requires further exploration.

The introduction of new manufacturing machines also affects both the production schedule and the pacing of activities on the production floor. The concept of *time* thus plays another relevant role for production processes. In their review of performance measurement systems, Neely and colleagues (2005) underlined that time has been traditionally described in the operations management literature as both a source of competitive advantage and the fundamental measure of manufacturing performance. Salvador, Forza, Rungtusanatham, and Choi (2001) maintain that shortening lead times and improving the timing of various activities has been the focus of operations management since the early studies on "just-in-time" (Sakakibara, Flynn, and Schroeder, 1993). In general, the adoption of flexible manufacturing systems aims at having an impact on lead-time reduction (Wadhwa, Rao, and Chan, 2005), for instance, by decreasing set-up and changeover time, and improving scheduling (i.e., the sequencing of activities), and workload balance.

More recently, literature has predicted time and cost savings with the introduction of new generations of flexible technologies, such as AM (Attaran, 2017). However, from a time-related perspective, the implications of implementing AM require a deeper understanding, as their technological limitations preclude better speed performance in comparison to traditional systems. Moreover, despite being measurable, time remains an intangible, subjective element. Yet, when discussing the physical production processes, the operations literature still provides limited evidence related to the cognitive implications of different perceptions of time, while a stronger focus is usually given in service operations (Nie, 2000)—for example when considering the psychological perception of waiting time. Hence, it is becoming increasingly important to learn more about this specific phenomenon, and its pivotal influence on routines in production processes.

Manufacturing Flexibility and Performance: From "Hard" to "Soft" Elements

Perez-Perez, Bedia, Lopez-Fernandez, and Garcia-Piqueres (2018) have argued that there is still ambiguity on the role and effects of manufacturing flexibility on individuals and organizations' performance. Firms are unlikely to obtain disruptive results from the stand-alone adoption of flexible manufacturing technologies if these technologies are not supported by design-manufacturing integration (Swink and Nair, 2007).

When considering the specific adoption of new production machines (also referred to as "manufacturing configuration"), scholars suggest a consideration of the "fit" within the specific context of application and its related features (Perez-Perez et al., 2018). For instance, the classic "product-process" matrix developed by Hayes and Wheelwright (1979) provides useful guidelines to classify different technologies along several degrees of manufacturing flexibility, ranging from production lines (characterized by a standardized structure with high volume, low variety, and high rigidity) and cellular-based manufacturing (where flexible systems play a key role), to job shops (processes in which small batches of a variety of customized products are made) and individual projects (featuring higher adaptability and opportunities for customization, but limited efficiency). However, in applying specific frameworks to manufacturing flexibility, a common approach in recent reviews is to use a number-driven approach to identify critical hold-ups (i.e., often supported with granular quantitative analyses and measurements), and suggest changes for sizable process optimizations (Jain et al., 2013; Mishra et al., 2014). Within this approach, scholars have mainly focused on "space" and "time" dimensions by adopting a numerical, engineering-oriented perspective, conceptualizing space and time as finite, tangible, measurable, objective resources, in order to provide recommendations to improve efficiency and effectiveness (for an example of such an approach, see the review on performance measurement system design by Neely and colleagues, 2005). In other words, space and time are investigated as mere operational factors that characterize a manufacturing/service process and its performance implications (the Online Appendix provides a table that summarizes how space and time are explored in the operations and manufacturing literature).

Scholars have also argued that to maximize the performance of flexible machines, it is key to understand the relationships among manufacturing flexibility, innovation processes (Bolwijn and Kumpe, 1990; Oke, 2013), capabilities (Camisón and López, 2010), and the appropriate combination of the so-called "soft elements" in the firm's organization and strategic orientation (Cagliano and Spina, 2000; Nambisan, Lyytinen, Majchrzak, and Song, 2017). Above all, scholars lament a scant understanding about the micro-foundations (i.e., actions, interactions, proto-routines), which favor the development capabilities at the firm level (Hayes and Wheelwright, 1979; Teece, 2007). For example, building on former perspectives (Zhang, Vonderembse, and Lim, 2003), Eyers and colleagues (2018) reflect on AM flexibility and their implications both inside and outside the firm's boundaries, highlighting that human skills are necessary requirements to operate and manage such technologies.

Our work claims that the traditional quantitative approach has thus far overlooked what Cagliano and Spina (2000) refer to as the "soft elements," that is the subjective and less-measurable aspects that complement our current understanding of how manufacturing machines can affect perceptions and routines related to the use of space and time in the production process. Specifically, this has limited our understanding in at least two ways. First, there is a scant understanding of how increasingly flexible manufacturing technologies, rather than serving as just passive tools and assets, can play an active role in reshaping space, time, and human interactions (Nambisan et al., 2017). This study posits this is one of the reasons why some recent issues in digital machine implementation remain unresolved, and present critical challenges impacting several companies—as reported by academic (Mellor et al., 2014) and industry experts (Deloitte Report, 2019). Second, behavioral elements, especially routines, have been considered in terms of performance impact, rather than a substantiation of human-machine interaction and their related cognitive implications (Howard-Grenville, 2005; Patel, 2011). This study aims to broaden our understanding of soft elements in the adoption of increasingly flexible manufacturing machines by responding to recent calls to adopt perspectives in fields outside of operations management (Khajavi, Holmström, and Partanen, 2018; Pagell, Klassen, Johnston, Shevchenko, and Sharma, 2015; Weller et al., 2015). Specifically, our aim is to explore routines from a more "micro perspective" (Felin et al., 2012; Gino and Pisano, 2008) that utilizes "behavioral viewpoints" (Aggarwal et al., 2017; Becker et al., 2005; Feldman and Pentland, 2003).

Toward a Behavioral Perspective in the Operations and Manufacturing Literature

Organizational routines: A definition. Within the Behavioral Theory of the Firm, Cyert and March (1963) defined "standard operating procedures," which today are better known as *routines*—following the more common term provided by Nelson and Winter (1982). A routine is a "pattern of behavior that is followed repeatedly, but is subject to change if conditions

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change" (Winter, 1964, p. 263). Routines are decision rules that are both precise production techniques and tacit strategic decisions, encompassing what is a predictable and stable behavior within organizations that derive from trial and error learning, as well as the selection and retention of prior successful behaviors (Aggarwal et al., 2017; Becker et al., 2005; Feldman and Pentland, 2003). Organizational routines have become increasingly important in the management literature not only because of their impact on firm performance, but also because of how a change in routine can affect performance (Feldman and Pentland, 2003). In fact, as routines tend to reinforce over time, they become the "genetic" (i.e., innate, essential) material of individuals and organizations' activities (Nelson and Winter, 1982). However, "many organizational routines are periodically, or even almost always, in flux. Indeed, a central proposition of routine theory is that organizations change what they are doing and how they are doing it by changing their routines" (Becker et al., 2005, p. 776).

The micro-foundations of organizational routines. Scholars have argued that changes in routines can be associated with different micro-foundations, defined as the causal explanation of routines and capabilities (Felin et al., 2012; Gavetti, 2005; Teece, 2007). In other words, micro-foundations are the building blocks of organizational routines (Felin et al., 2012). Micro-foundations can be clustered into three overarching and interacting categories, or main components (Felin et al., 2012): (1) individuals and their local actions, which enact learning and repetition (Felin et al., 2012; Gavetti, 2005); (2) processes and interactions as patterns of routines (Becker, 2004; Pentland and Rueter, 1994); and (3) structure and design, that contribute to the emergence of collective constructs. These three components have a hierarchical order and mutually interact, thus fostering the emergence of more or less adaptable routines (Felin et al., 2012).

In particular, an important type of interaction between individuals and processes involves technology and material artifacts. Many studies have investigated the effect of this interaction, highlighting how material objects shape the generation and the change of routines through adaptive learning (Bapuji, Hora, and Saeed, 2012; Cacciatori, 2012; Edmondson, Bohmer, and Pisano, 2001; Pentland and Feldman, 2008; Tyre and von Hippel, 1997). In fact, major technological shifts within a competitive domain (such as the emergence of flexible manufacturing technologies) require organizations to adapt by deploying resources that change the way their routines operate (Feldman and Pentland, 2003). When such changes lead to positive outcomes, individuals tend to perpetuate such behavior, enabling its consequent and underlying routine stability (Aggarwal et al., 2017; Loch and Wu, 2007).

The role of manufacturing flexibility in the development of organizational routines. Nevertheless, with the introduction of flexible manufacturing machines (which are characterized by adaptable outcomes and production processes), the development of new routines is required, thus forcing individuals to constantly redefine their behavior and to further experiment with the adopted technology (Loch and Wu, 2007). In this case, individuals mostly engage in a "trial and error" type of learning in order to identify a link between their choices, actions, and the related outcomes, as well as to ultimately stabilize their behavioral patterns (Edmondson et al., 2001; Loch and Wu, 2007). In other words, since flexible manufacturing machines promote experimental processes (due to the highly customizable functioning) they require the implementation of different alternatives to reduce causal ambiguity and assess the efficacy of individuals' actions (Becker et al., 2005). Therefore, increasing degrees of flexibility trigger changes in the micro-foundations of new routines. In summary, flexible machines not only create new routines, but they also enable changes in routines over time (Felin et al., 2012).

Given such nuances, the evolution of digital manufacturing requires a deeper investigation of its behavioral elements, echoing a recent call by Nambisan and colleagues (2017) to develop a stronger understanding about the cognitive and behavioral aspects of digital manufacturing. Within this context, the aspects related to the human actors' bounded rationality (Simon, 1982) still remain underexplored, and this is why the conversation on "behavioral operations" has received growing attention in the last decade. Perez-Perez et al. (2018) recently called for a more comprehensive understanding view on manufacturing flexibility, which should consider (among other aspects) behavioral elements involving individuals within organizations. The authors identify some studies which have engaged with topics such as workforce management activities (Urtasun-Alonso, Larraza-Kintana, García-Olaverri, and Huerta-Arribas, 2014), supplier involvement (Swink, Narasimhan, and Kim, 2005), quality management (Alolayyan, Mohd, and Idris, 2011), or resources for innovation (Camisón and López, 2010). Yet, the relation between behavioral aspects such as routine and cognition in relation to space or time remains under-investigated (Fahimnia et al., 2019).

Although traditional research in manufacturing has always acknowledged the important role played by workers in the production processes, Gino and Pisano (2008) maintain that the field has often considered people as deterministic, predictable, and emotionless actors. This implicitly assumes that people could be integrated into manufacturing or service systems like artifacts, with little or no adaptation to the new processes needed. In contrast with this traditional perspective, Loch and Wu (2007) promoted as an alternative view, the "behavioral operations management" view, a "multi-disciplinary branch of operations management that explicitly considers the effects of human behavior in process performance, influenced by cognitive biases, social preferences, and cultural norms" (p. 13). Additional key elements considered in the behavioral operations management perspective are factors at the interface between research on manufacturing and human resources, such as workers' skills, aspirations, and motivations (Boudreau and Robey, 2005), as well as emotions, culture, and individual differences (cf. the special issue edited by Croson, Schultz, Siemsen, and Yeo, 2013).

The emerging literature on behavioral operations management has mainly focused on cognition as a source of bounded rationality and cognitive biases that influence judgment and decision-making (Bendoly, Croson, Goncalves, and Schultz, 2010; Loch and Wu, 2007). Yet, our understanding of cognition is rather scant when it comes to situations where the individuals and groups interact with machines, how this interaction influences space and time perceptions, and ultimately the development and adaptation of routines. Specifically, because of their behavioral consequences, interactions with machines characterized by increasing degrees of manufacturing flexibility, and the consequent changes in the micro-foundations for the emergence of new and adaptable routines (Felin et al., 2012) deserve more scholarly and managerial attention.

By incorporating the lens provided by the Behavioral Theory of the Firm, this article addresses these research limitations in the fields of operations and innovation management. It aims to explore and investigate how varying levels of manufacturing flexibility affect firm routines in the production process, which still represent a "black box" in both literatures. In doing so, it focuses on space and time dimensions, as well as on the level of digitalization of the production process.

Method

Our study is developed through an exploratory, qualitative investigation, in which the adoption and implementation of 45 manufacturing machines of four different types within 14 companies in the British and Italian motorsport industry were compared. Our level of analysis is the industry, while our units of observation are the digital manufacturing machines, which are characterized by different levels of flexibility. This study does not aim to explain firm-specific variance across different organizations in the industry, but rather it identifies a general trend across various types of firms (e.g., assemblers, manufacturers, suppliers) within the same industry, and explores the variance across different types of digital machines with increasing degrees of manufacturing flexibility. The machines also possess different levels of digitalization; however, as articulated in the aforementioned literature and our own empirical observation, digitalization is not always correlated to manufacturing flexibility, in that it may or may not enable superior flexibility.

In line with methodological contributions for qualitative research (Barratt, Choi, and Li, 2011; Gioia, Corley, and Hamilton, 2013; Ketokivi and Choi, 2014), this study uses an inductive methodology (Glaser and Strauss, 1967; Locke, 2001; Strauss and Corbin, 1990) in order to investigate a theoretical question which was exploratory in nature (Edmondson and McManus, 2007). It tried to capture the opportunity to develop a deeper understanding of behavioral factors using observations of rich and meaningful real-world contexts—as underlined by Bendoly and colleagues (2010) and Schorsch, Wallenburg, and Wieland (2017), who have also highlighted the limited adoption of qualitative approaches in behavioral operations research.

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Empirical Setting

The suitability of the motorsport industry as the empirical setting for this study is due to its renowned manufacturing capability, which has traditionally favored technological experimentation to obtain superior performance (i.e., speed, reliability, safety) for innovative products (i.e., high-performing race/sport vehicles). The motorsport industry produces high-performing cars, motorcycles, and other types of vehicles (and related parts) either for racing competitions or for high-performance road models. Technological innovations developed in the motorsport industry are often transferred to standard vehicles, and scholars affirm that motorsport represents the acme of the automotive production (Schulze, MacDuffie, and Täube, 2015). Accordingly, several studies have chosen this informative field as a research setting (see among others: Aversa, Cabantous, and Haefliger, 2018; Aversa, Furnari, and Haefliger, 2015; Aversa and Guillotin, 2018; Bothner, Kim, and Smith, 2012; Castellucci and Ertug, 2010; Clough and Piezunka, 2020; Marino, Aversa, Mesquita, and Anand, 2015).

Despite operating on an approximately U.S. $4 billion international market, the manufacturing of high-performance motorsport vehicles is concentrated in two focal areas in Europe: the "British Motor Valley" located in the United Kingdom in a crescent-shaped area in the Midlands and Oxfordshire (Henry and Pinch, 2000; Tallman, Jenkins, Henry, and Pinch, 2004), and the "Terra dei Motori" (i.e., Land of Motors), a cluster of firms that extends along Emilia-Romagna in Italy (Jenkins and Tallman, 2016; Lipparini, Lorenzoni, and Ferriani, 2014).

Motorsport firms primarily focus on effectiveness (e.g., high-performance innovation, often geared to win races) but they also focus on efficiency (e.g., reducing costs to improve scalability for later mass production). For these reasons, firms often simultaneously pioneer new manufacturing technologies while adopting different types of machines, which overall provides different degrees of manufacturing flexibility on the production floor. For example, motorsport companies were among the first to adopt AM when it first appeared in the early 1990s and, unlike other sectors where AM implementation is still in its initial stage, motorsport companies are currently one of the most advanced sectors in their application of AM (Aversa, Massaro, and Lorenzoni, 2016). While in the early years AM machines were exclusively focused on rapid prototyping and cosmetic parts, they can now manufacture functional components for final products. All 45 machines have a digital core and handle digital inputs; for example, they all work via digital commands, process digital drawings, and provide digital reports of their activities. Yet, some of the more recently made machines (such as modern milling machines and 3D printers) use a significantly more advanced digital core, with advanced features such as cloud storage, design editing capabilities, and digitally driven optimization of the processes.[3] Given that the adoption of increasingly flexible digital machines (from single-component digital production lines to AM technologies) is a phenomenon spanning decades, choosing this industry enables the comparison of the parallel adoption of various types of machines (rather than their progressive substitution), which represents a clear advantage for our research design. In addition, the fact that the motorsports industry adopted the first AM technologies in the 1990s allows us to relax concerns related to the initial adaptation of routines due to the arrival of new technologies, which could be independent from their "flexible nature".

This study combines the observation of manufacturing flexibility, space, and time as objectively measurable phenomena with their behavioral aspects (related to subjective interpretations, cognition, and relational interaction among workers). Specifically, it adopts a behavioral perspective to explore how different (i.e., increasing) degrees of manufacturing flexibility are associated with different uses and perceptions of space and time, which are connected to different types of routines. In doing so, it extensively reflects on the important but under-explored implications for digitalization on the production floor.

[3]AM technology/3D printing is based on *additive processes*, where successive micro-layers of material are progressively deposited in order to form different solid shapes. 3D printing differs from traditional machining techniques that mostly rely on the removal of material by methods such as milling and drilling—which are generally called *subtractive* processes. The key contribution of additive technologies is related to the possibility to build incredibly complex shapes that were impossible to create with milling machines (Wagner and Walton, 2016). The layering involves a broad but still limited range of wax, plastic, composite materials, organic tissues, as well as metal powders. Yet despite a broader flexibility in manufacturing shapes, AM's physical, mechanical, and chemical properties are often inferior to those provided by casting, high-pressure mold injection, and CNC milling. For this reason, AM emerged (and it is still mostly used) for (rapid) prototyping, highly customized parts, and small production batches, rather than mass/serial production.

Table 1. Machine Sample and Company Features

Company	Main Areas of Activity Considered	Location	Number of Machines Per Type				
			a	b	c	d	Total
1. CRP/Energica	Supplier of complex mechanical parts for Formula 1. Manufacturer motorcycles for Moto E	Modena, Italy	1	0	1	1	3
2. Dallara	Supplier of chassis and aerodynamic appendices for F1, GP2, Indy500, Formula E, and high-performance road cars. Engineering consultancy	Parma, Italy	0	0	1	2	3
3. Ducati	Motorcycle manufacturer and racing team for MotoGP and SBK. Road motorcycle manufacturer	Bologna, Italy	0	1	0	2	3
4. Durango	Racing team in GP2 and Autocar	Venice, Italy	0	0	1	0	1
5. Ferrari	Formula 1 and GT car manufacturer and racing team; Sport car OEM	Modena, Italy	0	0	2	2	4
6. Grimeca	Supplier of braking systems	Rovigo, Italy	1	1	1	0	3
7. Tenneco	Supplier of shock absorbers	Bologna, Italy	1	1	0	0	2
8. OZ	Supplier of wheels		1	1	0	0	2
9. Poggipolini	Supplier of engine parts and carburetors	Bologna, Italy	2	2	1	0	5
10. Toro Rosso	Formula 1 car manufacturer and racing team	Faenza, Italy; Bicester, UK	0	0	1	1	2
11. Triumph	Motorcycle manufacturer; Tourist Trophy racing team	Hinckley, UK	1	2	2	1	6
12. Williams	Formula 1 car manufacturer and racing team. Engineering consultancy	Grove, UK	0	0	1	1	2
13. McLaren	Formula 1 car manufacturer and racing team Sport car manufacturer. Engineering consultancy	Woking, UK	1	1	1	2	5
14. Renault	Formula 1 car manufacturer and racing team	Enstone, UK	0	1	1	2	4
			8	10	13	14	45

Note: Types of machines: (1) Machines standard, "off-the-shelf" products, (2) Co-designed product-specific machines, (3) CNC milling machines, (4) Additive manufacturing machines (3D printers).

To provide a fairly representative assessment of the motorsport industry and to avoid biases derived from specific product specialization, a representative sample of machines was selected across a variety of companies involved in (1) different types of racing categories (e.g., Formula 1, Formula 2/GP2, Indy500, Le Mans, Formula Electric, Moto GP, Superbike etc.), (2) roles in the supply chain (e.g., vehicle manufacturers, part suppliers, racing teams), and (3) products (e.g., cars, motorcycles, specialized mechanical parts). See Table 1 for more details on the sample of companies that hosted the machines under investigation. Our sample of 45 machines thus combines the need to observe such phenomenon through a qualitative, exploratory lens and utilizes extensive sampling (considering the usual protocols of case study research). Indeed, while the focus on a specific, high-tech industry allows us to reduce variety in the scope of our findings, the wide array of organizations allowed us to reduce concerns related to specific arrangements that might be idiosyncratic within individual cases, and—with all the limitations of qualitative studies—extend the generalizability of our findings.

Sampling and Data

Specialized press and literature were initially explored to identify different types of digital manufacturing machines currently used in motorsport firms. A literature review was conducted to gather timely insights and focus our search, paying particular attention to new trends in manufacturing, such as the diffusion of flexible manufacturing. For the literature review, a selected collection of 101 documents was considered. Through informal conversation with four anonymous industry experts in Italy and three experts in the UK, four types of machines were identified and classified using the "product-process" matrix by Hayes and Wheelwright (1979) to consider different levels of flexibility and appropriate technological solutions for a variety of product/process configurations.

Two authors intimately familiar with the empirical setting retrieved the most complete address list of the motorsport companies with manufacturing facilities in the UK and Italian motorsport industry. The two authors contacted the companies via email explaining the aim of the study and asking if they would be interested in participating. Motorsport is a very secretive and fast-paced setting where it is difficult to collect data. Around 27 companies demonstrated some interest in participating and were visited for an introductory meeting. Ultimately, 14 were selected based on their relevance and technological features (established companies with active operations and manufacturing), as well as their availability for the interviews and prolonged observations. There were thus 48 total visits, including the aforementioned 27 introductory meetings. As a result, each plant and company in the sample was visited 2-3 times.

While the study had no quantitative component, our sample has a balanced representation of the different kinds of digital machines and includes a representative overview of the main types of firms in the motorsport manufacturing industry: (1) part suppliers (e.g., Dallara for chassis and composites, Poggipolini and CRP/Energica for mechanical parts, Grimeca for brakes and other engine parts, OZ for wheels), (2) motorcycles (e.g., Ducati in MotoGP and Superbike; Triumph for Superstock and Tourist Trophy races; CRP/Energica for Tourist Trophy and MotoGP electrical racing bikes), and (3) cars (e.g., Dallara in GP2 and Formula 1; Durango in GP2; Ferrari in Formula 1 and GT; Scuderia Toro Rosso, Renault, McLaren, and Williams in Formula 1). Our unit of observation was each individual machine, and the sample of machines observed was grouped across four different types based on their application to motorsport manufacturing, given their increasing manufacturing flexibility. After learning and understanding the main features of each machine and clustering them across the aforementioned "product-process" matrix by Hayes and Wheelwright (1979), a series of preliminary conversations were started with the company executives in charge of manufacturing decisions and implementation. In our study, a total of 45 different manufacturing machines across 14 firms were analyzed. Said machines were sorted into four major categories, which were not theory-driven, but in line with inductive research principles (see Gioia et al., 2013) they were defined using categories commonly employed by motorsport executives: (1) standard production machines for "off-the-shelf" products/components (8 machines); (2) custom-made, product-specific machines (10 machines); (3) CNC milling machines (13 machines); (4) additive manufacturing machines (14 machines). A table summarizing the features of the four types of machines is available in the Online Appendix.

Once the machines were identified, a series of semi-structured interviews were conducted (for a total of approximately 59 hours of interactions) with several employees of the companies who were involved with the selection, installation, and use of the machines. To avoid biased interpretations, at least two employees were interviewed in each company, specifically, both managers and workers who were involved with the machine—for example, R&D and production directors; operations managers; CEOs; specialized technicians and, when available, line workers. The interviews were used to discuss with the expert informants how the arrival of the machines changed their related activities. As some informants required anonymity, all interviewees' identities and quotes have been anonymized. Table 2 provides an overview of our anonymous informants.

As they were fairly complex and technologically advanced, most of the observed machines were usually operated by qualified workers with higher education, often with a university degree in engineering or technical subjects. In most cases, the scholars were granted access to the shop floor for observation and allowed to interview production line managers for further clarification. In some cases, the firm's executives also agreed to reveal and involve the machine manufacturer (i.e., sales managers and industrial designers working for the companies that supplied the machines), and some of their industrial customers (i.e., business-to-business clients) that purchased and/or co-developed parts and vehicles manufactured with that machine. Involving third parties allowed us to broaden our understanding of how the machine affected relations between agents involved in the machine's design, installation, and use, as well as cross-check some of the insights from the firm's managers.

For each machine, a round of semi-structured interviews on-site at the companies was conducted, as well as at least one round of interviews over the phone (when facing difficulties in reaching the firm plants). Our questions aimed to identify how the interaction with the machine and the cognitive understanding of the machines affected the use of space within the organization, the perception of time, and the routines related to the machines themselves. Our semi-structured interviews focused on five topics: (1) the position of the machines in the production plant, and modifications of the plant to accommodate the machine; (2)

Table 2. Grounded, Inductive Coding: First-Order Concepts, Second-Order Themes, Aggregate Dimensions

Type of Firms	Type of Role	Professional Role	Number of Informants	Types of Interactions
Motorsport firms in the sample	Top managers	Entrepreneurs/Presidents	6	• Exploratory phone calls
		Chief executive officers	8	• Semi-structured interviews
		Chief operating officers	8	• Informal interactions
		Chief technical officers/Technical directors	12	
		Chief information officers	6	
		Research and development directors	10	
		Production directors	14	
		Human resource directors	3	
		Operations directors		
	Middle managers	Purchasing managers	10	• Exploratory phone calls
		Operations managers	7	• Semi-structured interviews
		Logistic managers	8	• Informal interactions
		Account managers	9	
		Plant managers	14	
		Product managers	6	
		Project managers	5	
		Production managers	14	
		Operations managers	11	
	Employees	Designer/Engineers	10	• Semi-structured interviews
		Machine supervisors	32	• Informal interactions
		Machine workers	14	• Direct observation at works
Machine suppliers	Top managers	Sales directors	3	• Exploratory phone calls
	Middle managers	Sales manager/Account managers	4	• Semi-structured interviews
		After-sales managers	2	• Informal interactions
Firm's clients/ partners	Top managers	Chief technical officers/Technical directors	2	• Exploratory phone calls
	Middle managers	Product managers	6	• Semi-structured interviews
		Project managers	4	• Informal interactions

Note: Professional titles across firms have been adapted for comparable roles. Individuals often covered more than one professional role of those listed; "number of informants" should thus be considered as number of roles interviewed. Each type of interaction is listed if applicable to at least one of the informants within each professional role.

the use of the machine, with particular attention to the routines related to space and time; (3) the employees' narratives and perceptions about the use of space and time in relation to the machine adoption; (4) the changes to routines in relation with external parties (i.e., suppliers and clients); (5) the changes in performance outcomes that could be ascribed to the use of the machine (e.g., design and production time; product quality; clients' satisfaction). The latter point was the one explored the least, given it is a very complex topic, hard to assess in qualitative terms, and fell outside the central scope of our investigation. The direct observations consisted in two types of activities: (1) guided tours of the production facility with explanations given by the company's managers and (2) independent observation of the machine "in action." For the second type of observation, one of the researchers sat for several hours to observe workers in action and took notes/sketches to report the development of activities between employees and third parties. In both cases, attention was dedicated to routinized interactions with the machine, production of supporting documents, and artifacts.

In addition, available company archival materials that related to the machine were inspected (i.e., catalogs, manuals, samples, instructions, sketches, machine and plant blueprints, working notes, meeting reports, etc.); a total of 233 document were reviewed (more than 2500 pages), then reduced to 136 relevant documents (around 1300 pages) that were used to identify differences in the nature of these documents/artifacts vis-à-vis the different types of machine. As these documents were essential to the companies' activities, it was often not allowed to take or copy them, but only to observe them and take notes. Further, whenever possible, pictures, small videos, sketches of the locations where the machines were placed (to understand how location design and use varied vis-à-vis each type of machines) were taken. When possible, in order to compare our inductive observations to more traditional research protocols in operations literature, quantitative descriptive data were collected, identifying for example the number of workers dedicated to each phase of the machine's life. This included, for instance, the average number of additional documents created to support the use and understanding of the machine, and the number of agents involved in each phase of the machine lifetime. These measures helped us achieve an overall understanding of the machine's functioning. Yet, as our study is focused on "soft aspects," a summary table of these main aspects is provided in the Online Appendix.

Data Coding and Analysis

Following the common protocols of qualitative research (Yin, 2008), our data went through a multistage selection process, where the two scholars ranked the collected evidence in terms of interest, consistency, and relatedness to the topic of the inquiry. When minimum standards were not identified, files and documents were discarded, while others were considered only in part. Our data were analyzed through an inductive process that helped us bring "qualitative rigor" to the analysis (Gioia et al., 2013, pp. 20–21). This required examining explanations in light of the empirical evidence, while inferring theoretically relevant constructs, often in a recursive way between data and theory.

Starting from our semi-structured interviews as the main source of data, as suggested by Gioia and colleagues (2013), a fine-grained and intensive reading of the interviews were developed (Strauss and Corbin, 1990), which resulted in a large dataset of terms and codes. Redundancies were iteratively consolidated and, following the steps of the aforementioned methodology, they were collapsed into 20 first-order concepts. A sample of significant quotes leading to first-order concepts can be found in the Online Appendix. For each first-order concept, a small "title" and short description were jointly identified. Throughout the entire process, frequent referral back to our archival data and notes from our observations happened to make sure that no information had been omitted or misinterpreted.

Our 20 first-order concepts were compared with the classified data from prior research and started structuring the concepts into a final selection of four second-order themes, and later into two higher-level aggregate dimensions (Gioia et al., 2013, pp. 20–21). During this process, the scholars progressed toward a more theory-driven explanation of the first-order concepts. To obtain a relevant interpretation of our data, iterations through this step several times and the making of extensive use of notes and personal observations were made, going back-and-forth between emergent data, themes and concepts, and one of the scholars challenged the interpretations, playing the "devil's advocate" role (Van Maanen, 1979). Subsequently, a data structure was built that represents how the abstraction exercise progressed from raw data to terms and themes, providing a visual representation of this process. Finally, a testable conceptual framework of the relations between the emerging elements was designed.

The remaining data were later analyzed through comparative tables, which followed the methodological protocols for inductive qualitative comparative studies (Glaser and Strauss, 1967; Strauss and Corbin, 1990). Tables were built by identifying the significant measures for the scope of our inquiry, mainly by classifying and measuring use of time and space. Also, significant quotes were selected, and discussed among the scholars to identify a consistent interpretation of the interviewees' opinions (Yin, 2008). A selection of the most significant quotes is reported in the article in support of our analysis.

Table 3 presents the structure of the inductive coding, as per Gioia et al. (2013), which moves from first-order concepts to abstracted second-order themes, and ultimately to aggregate dimensions. Our narration will summarize our observations by following this abstraction path from evidence to theoretically relevant constructs.

Results

Space-Machine Routines

Despite traditional manufacturing and innovation literature, which often considers machines as passive sets of tools or assets that workers use and adapt to their objectives, the collected evidence suggests that manufacturing machines also play an active role in shaping the operational space where innovation and manufacturing takes place. Figure 1 offers a simplified

Table 3. Grounded, Inductive Coding: First-Order Concepts, Second-Order Themes, Aggregate Dimensions

First-Order Concepts	Second-Order Themes	Aggregate Dimensions
(1) *Space redesign*: The machine is associated with significant redesign of the operational space	(a) Reshaping of the interactive *space* around the machine	(i) Space–Machine Routines
(2) *Spaces for experimentation*: The machine drives the development of new spaces for experimentation and innovation		
(3) *Improvement or space access and exit*: The space where the machine is placed is designed (or modified) to facilitate customer access and exits (double entrance/exit)		
(4) *Co-location of design and manufacturing activities*: With the arrival of the machine, the design activities move near the machine, the machine enters the design office		
(5) *Instructions and notes populate the space around the machine*: The experimentation space presents sketches, instructions, and additional guiding materials		
(6) *Advanced samples are showcased in the machine space*: The space where the machine is placed contains "advanced manufacturing samples" to show the machine potential and inquire into new solutions		
(7) *Machine space as connecting space across partnering organizations*: The machine space becomes the shared experimentation space for different technological partners	(b) Reshaping of innovation activities performed in the machine space	
(8) *Increasing co-development*: The experimentation potential of the machine calls for physical co-presence of partners in the (co)working space		
(9) *Machine as "totemic" element in the manufacturing space*: The machine acquires physical and metaphorical primacy on the shop floor		
(10) *Machine centrality to favor interaction from multiple sides*: The position of the machine improves the ability to walk around the machine and operate/observe it from multiple sides		
(11) *Machine access as sign of trust toward third parties*: Accessing to the area where the machines are placed corresponds with a demonstration of trust toward the customer/partner		
(12) *Time shift from set-up to experimentation*: The machines extend the interaction time in the experimentation phase and reduce the interaction time in the setting up phase	(c) Reshaping of *time* within activities involving the machine	(ii) Time–Machine Routines
(13) *Time shift from manufacturing to experimentation*: The machines extend the interaction time in the experimentation phase and reduce the interaction time in the manufacturing phase		
(14) *Time increase in monitoring activities*: Reduced automation of flexible machines forces workers to dedicate greater time in monitoring the machine		
(15) *Machines determine the time for the firm projects*: The operational time of the machines shapes the project pace, its timing, and deadlines		
(16) *Partners' time alignment to the machine schedule*: The timing of the project among the various partners aligns to the timing of the organization owning the machine		
(17) *Machines bring new narratives of "time" and "speed" to the organization*: The adoption of the machine corresponds with a new narrative of time for the intervening partners (speed, responsiveness)	(d) Reshaping of *time* perception	
(18) *Actors' cognitive association between the machine flexibility and time efficiency*: The adoption of the machine is cognitively associated with reduced operational times		
(19) *Trade-off between project delays and superior outcomes*: Time in experimentation tends to extend beyond the planned schedule, but this overall increases the overall output quality and third parties rarely interpret it as a limitation or a major issue		
(20) *Difficulties in distinguishing experimentation time from manufacturing time*: With functional prototypes, the experimentation time blends into the manufacturing time. Actors struggle to clearly separate the two, making their development phases incomparable to former projects		

representation of how the use of space in the production plant changes as the four types of increasingly flexible machines are introduced (each phase corresponds to a different type of machine).

Our first order-concepts point to a *reshaping of the interactive space around the machine*. For the observed projects, it was noticed that when a new machine entered the production space, the introduction

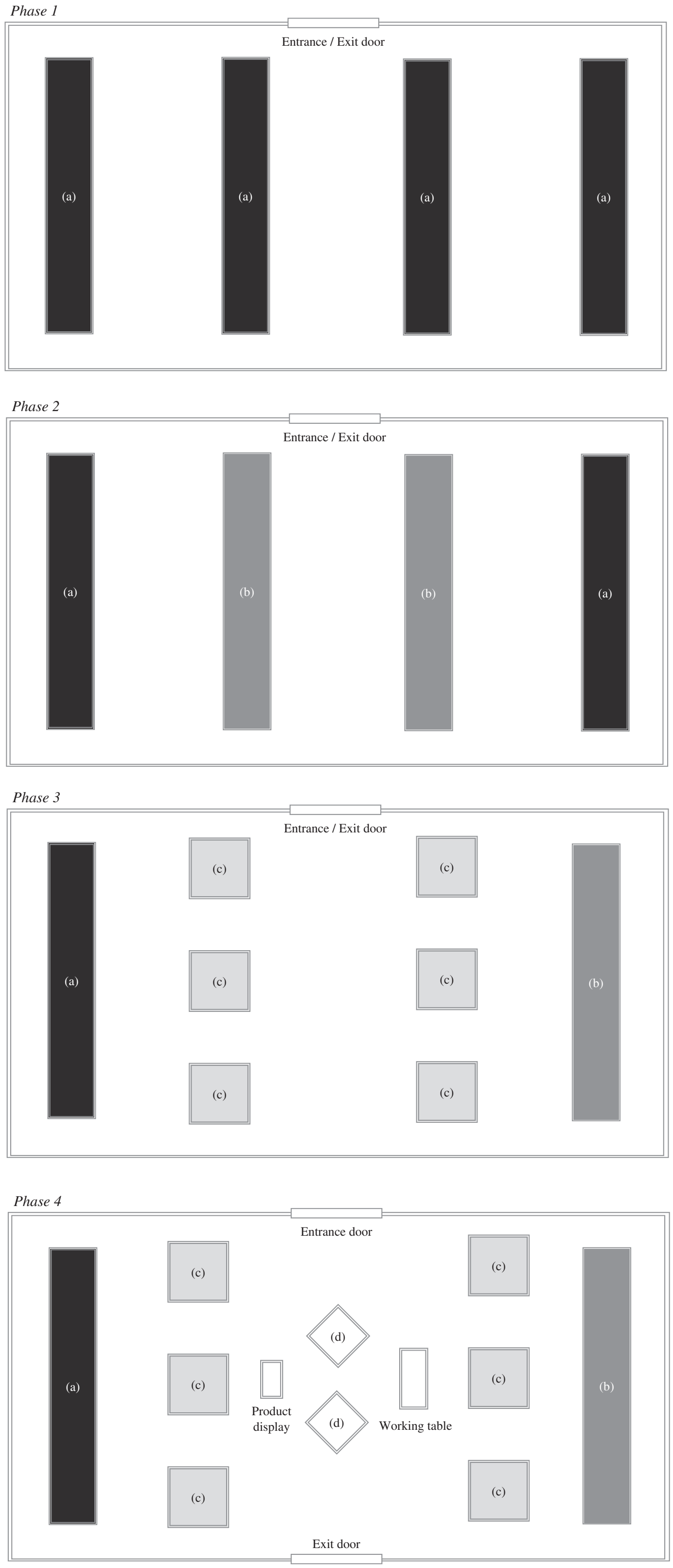

Figure 1. A Representation of the Space Reorganization Given the Progressive Introduction of Increasingly Flexible Machines.
Note: Each phase corresponds to progressive introduction of a new type of machine. Types of machines: (1) machine standard, "off-the-shelf" products (black), (2) co-designed product-specific machines (dark gray), (3) CNC milling machines (light gray), (4) additive manufacturing machines—3D printers—(white)

was associated with a redesign of the operational space layout, and employees were involved to optimize routines and collective procedures. This interactive space represented not only an intangible “discourse” between individuals involved in the operations, but often translated—particularly for more flexible machines—into an opportunity to set up specialized areas, such as R&D labs, customer trial rooms, and other spaces dedicated to idea generations. The Online Appendix provides data on the average number of experimental spaces dedicated to each type of machine. Evidence illustrated that as the level of flexibility increased, there were a greater number of such dedicated spaces.

The use of space revolved around the work of the technological equipment that, when possible, involved external third parties (i.e., suppliers, partners, clients). In such cases, experimentation with the machine was used to gather new knowledge via search and trial-and-error. In such instances, it was common to witness either the move of some of the design activities to the production floor, where the experimenting machines were located, or when size of the machine allowed, the manufacturing machine was placed in the offices dedicated to the design activities.

Evidence showed that custom-made product-specific machines (and in general, less flexible machines) were progressively cornered at the sides of the production floor, while the most flexible machines occupied more central positions—closer to entrance and exit doors (see Figure 1). More importantly, less flexible machines were less likely to be associated with initiatives that were collaborative or experimental. Interviewees suggested that this was due to the manufacturing rigidity of such machines (e.g., lines for specific products). For example, when it was asked why there were set no areas for experimentation connected to these machines, managers responded:

> *These tools leave no space for experimentation, nor creativity. They do one thing, and they do it well, fast, and cheap. But one cannot move away from that. It makes no sense investing in experimenting in something with little or no potential for innovation. (R&D director)*

Machines with increasing flexibility tended to play a more dynamic role in shaping the virtual and physical space around them, thus creating opportunities for interaction, knowledge exchange, and experimentation. This was systematically associated with the co-presence of partners and customers within the interaction space, making the production floor where the machine operated a connection point between the production facilities of multiple stakeholders involved in the co-development project. As CNC and AM machines offered a broad and not fully understood range of possibilities, companies that used such technologies enjoyed the opportunity to upgrade the understanding of their functioning, and thus enlarged their types of manufacturing applications. Among other less notable aspects, the space was specifically designed (or modified) to facilitate the access of customers and partners in order to maintain a high level of discretion about their involvement, particularly toward other customers and third parties who could be competitors. Figure 1 (phase 4) illustrates how the introduction of AM technologies corresponded to the creation of an exit door, which forced visitors and operators to pass by (and be exposed) to the machine and its dedicated working space. By showing careful attention to such space design, the focal company aimed at obtaining a high level of trust from each partner.

> *Here we place our 3D printers (indicating the machines). Customers enter from that door and interact here with our technicians. They discuss problems, launch production of new parts, and see us “in action.” Sometimes we also take them to the wind-tunnel room. We also have a secondary door there so that one customer can get out without the next one seeing them. For our job discretion is key. (CEO)*

> *Once we had a misunderstanding and double-booked the machine for a technical trial with two different clients at the same time. Luckily we made the other customer exit from that door so that his competitor would not see him. (Worker)*

Evidence suggests that machine adoption also corresponds with a shift in the *innovation activities performed around the machine space*. In advancing this observation it is necessary to include two additional reflections. First, the increasing levels of flexibility corresponded to more significant changes in such activities—this, however, might be related to the fact that newer tools embedded possibilities and features that by definition disrupted those formerly established by the adoption of older machines. Second, and perhaps more importantly, the emergence of new activities was associated with a different perception of space, where the spatial areas were adapted to incoming flexibility needs to embrace more dynamic and unstructured experimentation activities. Our observations revealed that a space of active experimentation called for the needs of partners being present in the same area to conduct their co-development activities. Simultaneous presence transformed the area into co-working spaces, populated by desks and/or working tables that were used for meetings and workshops with workers and with business partners (see Figure 1, phase 4). In such areas, it was often possible to retrieve artifacts of such activities and interactions: sketches, blueprints, guideline documents, and instructions. Such material artifacts had a functional utility insofar as they indicated ways of utilizing the machine to more unaware users. Yet, their visible and tangible presence also attested to the amount of collective reasoning and trials that had been going into the engagement with the machine. Another key element that was common to find in the proximity of the machine was advanced manufacturing samples. In most cases, these were purposefully left to impress possible visitors or showcase the potential of the machine. Such elements, however, also held a subtle and perhaps more relevant function. As increasing levels of manufacturing allowed a much higher number of potential applications, such artifacts were used to demonstrate through material evidence the firm's creative capability and its skills in exploiting and exploring the machine potential.

> *This is, for example, a component we made with Windform [a material patented by the company]. As you can see this reticular structure would not be possible with injection molds nor with milling machines. This explains what our machines and materials do. (R&D director)*

In most cases, milling machines and to an even greater extent, AM machines, were placed in the center of the room or in a highly visible position where it was impossible not to notice them. They represented a sort of "totem" within the manufacturing space, such that they were regarded with a sort of admiration, respect, and curiosity (probably due to their untapped potential). This positioning was not necessarily based on layout optimization, but more to fulfill a symbolic function. Such machines could be observed from all sides, and visiting the machine with new partners often followed systematic patterns and "rituals," where the problem-solving value of the machine was described using a specific narrative of time.

Time-Machine Routines

Aside from space, *time-machine routines* emerged as another prominent element from our observations. Within our organizations of study, time was conceived not only in a more objective form, as a measurable and systematic repartition of human activities, but also as a subjective, cognitive construct derived from workers' perceptions, and thus took different forms, led to different understandings, and consequently affected the activities on the shop floor in different ways.

A set of ways in which time (e.g., sequencing, duration) was reshaped within routines involving the machine were identifies. To compare our observation with a more nuanced understanding of machine use, our informants were asked a series of question aimed at understanding (1) how many hours of work employees dedicated to the design and first set-up of the new machine; (2) how many hours they spent to understand its functioning and exploring its possibilities before considering the machine to be fully integrated in the manufacturing processes; and (3) what their overall perception was on how the use of time changed following the adoption of the machine.

These three distinctions were critical to helping us identify whether the interaction with the machine was concentrated in the planning, in the execution of the manufacturing process, or both. In addition, as the interaction with these machines might involve human agents from different organizations, inquiring into such aspects also provided insights about the temporal evolution of the interaction between the workers and the machine. Specifically, our interviewees were asked to quantify the hours spent in interaction with other members of the organization, other partners such as the equipment suppliers, or the customers. Values for each machine and averages across machine types were collected—a summary table with quantitative measures of machine usage is reported in the Online Appendix. Executives and operators were also asked to provide narratives of such phases. Our data collection highlighted that the intensity of interaction with the machine was strongly influenced by the machine's degree of manufacturing flexibility. While customized, task-specific machines (i.e., machines for standard, "off-the-shelf" products and custom-made, product-specific machines) led to more intense interaction in the machine design and set-up phase, standard flexible machines (i.e., CNC milling machines and AM machines) required a more intense interaction later on in the testing and operational phase. Throughout all our observations, interviewees consistently affirmed that for machines that were more flexible, human intervention was higher in the phases not strictly following defined procedures or routines:

> *Milling machines offer a lot of flexibility, particularly when considering a 5 axes mill, but 3D printing offers even more. We use these machines in different ways and we believe we are not fully exploiting their potential yet. For this reason, we are still working with the machine supplier to explore what the machine can actually do. Materials keep developing as well: with metal powders we can now manufacture functional parts that do not simply work for prototyping (…) but also for final products. Still, to understand how to achieve such results it requires a lot of time and interaction once we start using the machine. (Operations manager)*

As custom-made, product-specific machines and machines for standard "off-the-shelf" products did not offer any major opportunity for significant variation within the manufacturing process—unless the machine underwent a structural re-engineering—they required instead an intense human intervention while designing the machine itself, as the equipment came with a high level of customization.

> *We spent quite a lot of time trying to figure out how to make this sealing machine work. We wanted it to be fully integrated in the manufacturing line. This is quite a complex process and we need the machine to do it perfectly. We designed the machine with our machinery supplier. (Production manager)*

Evidence pointed to a different scenario for the application of more flexible machines (i.e., milling machines and 3D printers), as this equipment came in rather standard models, but provided greater opportunities for flexible application. Hence, while the design phase was relatively standardized, and left little space for customization, once the machine was set up, the possibilities of experimentation benefitted from an experienced and continuous interaction with the machine.

> *All people in my team working with 3D manufacturing have advanced skills in design as well. They are usually mechanical or aerodynamic engineers. Such machines require talent and experience, particularly for the applications we pursue for Formula 1. (Manufacturing director)*

All in all, it was noticed how the different levels of machine flexibility corresponded to different timings in the interaction process with the equipment. Activities enabled by highly flexible machines were often described as more "fragile" and likely to suffer from hold-ups. Despite the fact that such devices allowed for a certain level of automation, the employees felt compelled to monitor their activity more often.

> *We have very quick machines here. Even the 3D printers are some of the quickest on the market. But these are very complex machines too. A lot can go wrong. One always needs to monitor them. (…) Sometimes we make mistakes, and we struggle to match the delivery time of new parts for the race. Often our workers are required to do night shifts to solve these problems and deliver on time. (Qualified machine operator)*

The overall focus on the experimentation phase created a relevant shift in the timing of the innovation development, as the machine constraints and utilization paced the project timing and deadlines. However, as such machines were used as collaborative devices in multipartner experimentation, the alignment of the partners was also constrained by the timing of the machine. Thus, the firm deploying the machine ended up indirectly influencing the timing of the third parties involved.

Ultimately, the time-machine interaction carried significant implications on a more subjective and cognitive level. The adoption of more flexible machines corresponded to the adoption of new narratives of time within the organization. Concepts like "speed," "responsiveness," and "reaction time," became part of the core value proposition that the organizations embraced, particularly when proposing their services or potential collaborations to external actors. This shift is not surprising overall, as technological adoptions are often justified with aspirational upgrades in efficiency and effectiveness, particularly in innovation-focused domains. However, in our case, such types of narratives held substantial implications in the way time was envisioned and activities were scheduled. More flexible machines entailed the systematic extension of the experimentation phase (due to extensive set-up time, integration of multiple actors, and exploration of diverse operational possibilities), and as such, this narrative of time and "speed" was associated with an average reduction of estimated experimentation time in a range of −10% and −20%. This meant, for example, that a new design project that would have been estimated to last around 10 weeks with prior machines and technology was now expected to take between 8 to 9 weeks. Still, such estimates often fell short to deliver on even the original 10-week schedule. This did not negatively affect the quality of the output, as products developed with superior manufacturing flexibility usually resulted in superior innovation. Nonetheless, timing remained an unfulfilled promise in the relation with third parties. However, the external partners' direct involvement in the project allowed them to appreciate the nuances of the process and the superior returns that extended experimentation entailed. Ultimately, reasonable delays were seldom considered an issue, and they hardly terminated the partnership.

Furthermore, with increasingly flexible machines, the design and engineering of a component became a key element of each project. With the advent of harder materials in AM (e.g., through metal and graphene powders), companies were able to manufacture more and more structural components and functional prototypes. These were components which, despite their prototypical nature, could be deployed (within certain limits) in finished products such as a race vehicle, rather than just being used for cosmetic mock-ups and wind-tunnel models. The diffusion of "functional prototypes" blurred the boundaries between experimentation and production phases, and actors involved in the process struggled to more objectively divide and measure the two. This reconceptualization of time and project sequencing made former and current project development less comparable, thus the adoption of new machines lead to a paradigmatic shift in the manufacturing operations.

Discussion

The Role of Digital Technologies in Manufacturing Flexibility: A Behavioral Conceptual Framework

The operations and innovation management literature provides extensive documentation of the relation between technological adoption and manufacturing flexibility (Caggiano et al., 2015; Culot et al., 2020; Oke, 2005), manufacturing flexibility and firm performance (Grawe, Daugherty, and Roath, 2011; Youndt, Snell, Dean, and Lepak, 1996), and routines and performance (Abell, Felin, and Foss, 2008; Cohen et al., 1996; Felin et al., 2012; Levinthal and Marino, 2015). Yet little is known about the interplay between increasingly flexible manufacturing machines and behavioral elements related to the cognition of space and time on the production floor, and how this interaction affects the development and adaptation of specific routines. Accordingly, this is the focus of our attention and theoretical contribution.

In Figure 2, white arrows and boxes represent relations explored in the literature—reviewed in the theoretical background—while darker arrows and boxes identify the theorization derived from our investigation. In our conceptual framework, routines emerge as a mediation between manufacturing flexibility and firm performance. Increasing manufacturing flexibility more strongly affects the development of routines across the dimensions of space and time. In terms of space, this study shows how more flexible machines trigger a reshaping of the space to promote interaction, as for example, the undertaking of a more radical change in the layout of a shop floor. A more traditional operations literature would suggest a rational optimization of the layout aimed at minimizing movement of products and employees, yet there exist cognitive elements motivating layout decisions, such as in the case of AM machines positioned centrally as "totems," the inclusion of experimentation spaces, or the creation of dedicated display to display related artifacts (i.e., notes, instructions, advanced samples)—as per Table 3.

At the same time, more flexible machines reshape innovation activities in the production space by calling for the involvement of multiple actors, and a new set of interactions and routines in relation to the machine itself. Manufacturing flexibility also increasingly influences innovation activities over time. Not only are there changes in the schedule of machine-related

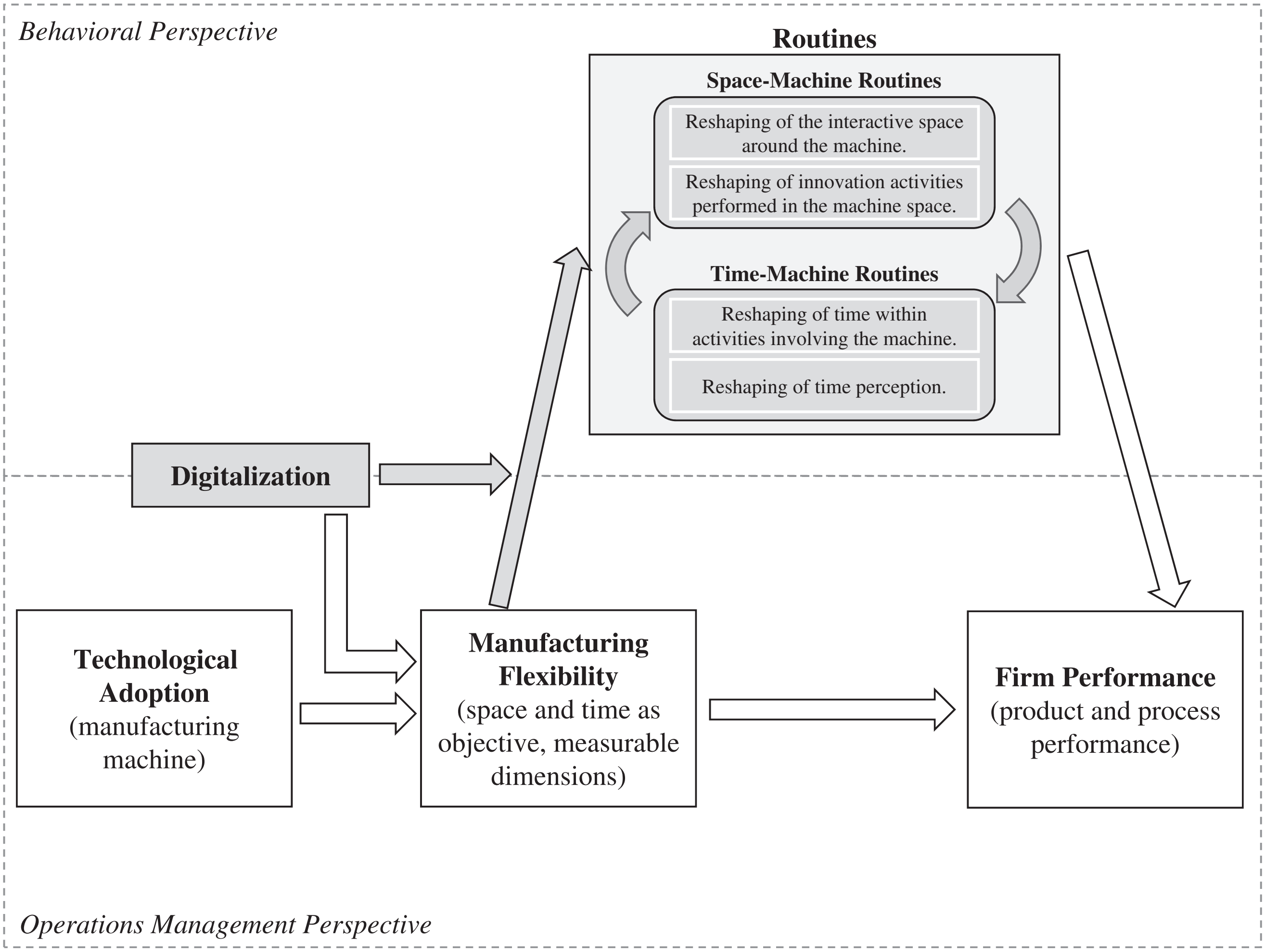

Figure 2. Conceptual Framework: Manufacturing Flexibility, Digitalization, and Routines.
Note: White shapes: elements from the literature review. Gray shapes: elements developed in this study

activities (e.g., superior experimentation and monitoring, all partners align to the time constraints of the machine), but relevant cognitive implications also emerge. Specifically, a new narrative of "speed" and "responsiveness" is embraced by the actors who utilize more flexible, and ultimately more efficient and better performing, machines. Although there is a systematic underestimation of the time scheduling necessary to complete a project, the positive effects of the digital machine adoption and the development of additional specialized activities can be witnessed in the increasing average quality of the product/process, due to more intense interactions with third parties (i.e., partners, clients, etc.). Yet it could be undermined by the necessary increased experimentation phase within the producing process. This finding is in line with the established literature on behavioral operation management, which highlights the role played by cognitive biases such as "over-confidence" in judgment (Bendoly et al., 2010), both in terms of "over-precision" (i.e., individuals believe they know more than they do) and an optimistic "overestimation" of abilities (related to using the digital technology).

However, our findings provide a novel understanding of such overconfidence biases, as well as unexpected implications overlooked in the operations and innovation management literature thus far. In fact, despite the increasing experimentation required by digital flexible machines, often resulting in systematic underestimation of the development time, it also increases the involvement of third parties in such extensive experimentation phases. In turn, the average quality of the product/process increases, insofar as partners see possible delays as necessary costs to achieve superior outcomes. Ultimately, this strengthens (rather than foregoes) interorganizational partnerships. Functional prototypes inhibit a clear separation between experimentation and production, thus requiring a new way to assess project times and compare them to older ones. Still, the possibility to apply components born in prototyping processes to final products reduces the complexity of the production process by eliminating the intermediate production phase that creates final parts from prototypes, ultimately enhancing product and process performances overall.

In addition, our findings related to cognitive implications of space and layout decision (for instance when the machine positioning is connected to an attempt to protect confidential partnerships) underline the importance of engaging with the behavioral nuances related to cognition of space and time. Our study suggests that there are not only individual and group implications, but also relevant interorganizational trust implications (Schorsch et al., 2017), which might reshape (and possibly enhance) the firm's relational capabilities with key partners (Lorenzoni and Lipparini, 1999).

The Role of Digitalization

Importantly, digital technologies play a key role in our conceptual framework, and shed light on aspects so far overlooked in the operations and innovation literatures investigating cognitive and behavioral implications. As a first premise, it is important to acknowledge that these days it is incredibly rare to find machines with a purely analogical interface in companies whose focus is on technological innovation and advanced manufacturing. The great majority of modern manufacturing machines (no matter how operationally flexible) embed a digital component or interface, such as data transmission systems for digital commands through project specs. This was the case for all the observed and assessed machines. Arguably, digital technology can be, therefore, considered endogenous to (and embedded in) the technological adoption, and one of the enablers of manufacturing flexibility (see the angled arrow in Figure 2). That said, it is also important to emphasize that the level of digitalization can also present variations across cases, which might depend on the firms' engagement with the digital technologies—for example, the level of digitalization of each machine (different machines can have a more or less prominent digital integration) and, perhaps more importantly, the level of digital transformation that each firm has embraced in its productive process and complementary or supporting technologies. In this regard, the digitalization plays a pivotal role in moderating (and enhancing) the relation between manufacturing flexibility and routines.

Digital solutions are in fact based on strings of data, which are, by definition, loosely coupled and more modular than physical artifacts (Baldwin and Clark, 2000; Ulrich and Tung, 1991). Digital interfaces can be more easily aligned to common technological standards and IT protocols, and it is, therefore, more efficient to recombine the layout of a manufacturing space if the different machines can be swiftly connected to standard digital interfaces (Kallinikos, Aaltonen, and Marton, 2013). Digital solutions allow for a superior level of process flexibility, thus enabling the reshaping of time across projects. In addition, digital solutions, despite being powerful and influential, are naturally intangible and immaterial—see for example software, digital files, blueprints, communication protocols, and digitally enabled decision support systems. The intangible nature of these elements—more pervasive in production contexts—makes them more apt to trigger perceptions that are cognitively different across individuals. For this reason, the digital component of manufacturing machines is not only an enabler of manufacturing flexibility (as claimed in the literature), but also a moderator of the relation between such flexibility and the establishment of new routines. This study posits an increasing level of digitalization to enhance the routine-based mechanisms that mediate the relationship between manufacturing flexibility and performance.

Conclusions

Recently, several scholars in operations, manufacturing, and innovation have been debating the importance of adopting a more "micro" perspective in understanding technological changes and implementation within organizations. It has been argued that a micro perspective is necessary to better understand the role of new technologies, such as the introduction of digitally enabled, increasingly flexible manufacturing machines, which have affected the ways individuals interact and operate (Dalenogare, Benitez, Ayala, and Frank, 2018; Fawcett and Waller, 2014; Holmström and Romme, 2012). Research is thus in need of better engagement with the *behavioral* implications of firms' activities and manufacturing processes (Gino and Pisano, 2008; Jain et al., 2013). In fact, when flexible manufacturing machines are introduced in the production process, individuals change their perception and use of space and time, thus shifting their routines on the production floor—aspects that complement the Behavioral Theory of the Firm (Cyert and March, 1963). By anchoring our empirical exploration on a comparative study of 45 different machines (over four different types and 14 companies), our work aims to embrace a *behavioral perspective* to provide a set of key insights for academics and practitioners.

Contributions to the Academic Literature

First and foremost, drawing from previous studies in operations and innovation management based on a behavioral perspective (e.g., Bendoly et al., 2006, 2010; Colarelli O'Connor, 2008; Croson et al., 2013; Gino and Pisano, 2008; Kavusan and Frankort, 2019; Michael and Palandjian, 2004), this study provides a novel understanding of the relationship between varying levels of manufacturing flexibility provided by digital machines on the production floor and the subjective dimensions of human interaction related to space and time, addressing an understudied relationship in the literature. In doing so, it extends and complements the traditional and extensive stream of works on manufacturing flexibility (see among others, Koste and Malhotra, 1999; Slack, 1987; Zhang et al., 2003) by providing insights on the interaction between humans and machines. In fact, despite having underlined the complex, multidimensional nature of the manufacturing flexibility concept (Perez-Perez et al., 2018), the operations management literature investigating the evolving phenomenon of the digital transformation in the context of Industry 4.0 has thus far overlooked important behavioral elements, including routines in the production process. With our empirical endeavor, this study moves beyond the established issues generally considered in behavioral operations—mainly decision-making and judgment issues (Bendoly et al., 2010), and human resources-related issues (Boudreau, Ramstad, and Dowling, 2003)—to incorporate a novel understanding of the routines related to space and time. It underlines the opportunity to combine several perspectives (i.e., individual, group, and inter-organizational, as suggested by Bendoly et al., 2010; Schorsch et al., 2017) to evaluate the implications of these behavioral elements.

Second, it specifically provides the first granular investigation of the interaction between manufacturing technology, cognition, routines, and the changes in their micro-foundations, by developing a novel conceptual framework, focusing on two key domains related to the Behavioral Theory of the Firm (Cyert and March, 1963): space and time. In doing so, this study extends a perspective at the interface between operations and innovation management literatures, where space and time are often analyzed exclusively as quantifiable and measurable dimensions. For the space dimension, our framework underlines the *re-shaping of the interactive space around the machine*. It is worth nothing that when increasingly flexible machines enter the manufacturing production plant, they tend to occupy very visible, central areas within the facility, thus indirectly influencing the location of other types of (less flexible) machines. This aspect also extends to the *reshaping of innovation activities performed in the machine space*. In fact, evidence also suggests that digital machine flexibility is increasingly associated with dedicated spaces for experimentation within manufacturing plants (e.g., customer trial centers, R&D labs). More flexible machines thus provide a space for experimentation and innovation, which offers opportunities for interaction between company employees as well as external partners. Our results underline the potential offered by increasingly flexible technologies in creating the opportunity to enhance the interaction and collaboration with partners and customers (Mellor et al., 2014). In line with previous studies (Holmström and Chaudhuri, 2017; Holmström, Partanen, Tuomi, and Walter, 2010), this article posits that customers of digital flexible machines might benefit from greater service levels as production may be not only decentralized (and thus occur closer to the customers), but also more likely to directly involve them in the manufacturer's production process.

Third, evidence suggests that the time dimension is also significantly affected by increasing machine flexibility. Our conceptual framework highlights the *re-shaping of time within activities involving the machine*. In other words, machines with superior manufacturing flexibility require managers spend more time experimenting with the new technologies in order to fully understand how to maximize their manufacturing potential. Less flexible (i.e., more task-specific) machines need to be ex-ante fully integrated in the manufacturing processes and their design is often precisely developed to maximize this aspect. Accordingly, it is worth noting that as machine operational flexibility increases, the time

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dedicated to the machine moves from the design and set-up phase to the actual operation and experimentation with the machine. For instance, in line with Holweg (2015) and Holmström, Holweg, Khajavi, and Partanen (2016), our results confirm that 3D printing fundamentally does not happen "at the touch of a button." While the diffusion of AM technologies means firms can access such machines at more convenient prices, an effective adoption might involve considerable experimentation and processing, which in turn could have non-trivial labor cost implications. This is also connected to the need to consider the *re-shaping of time perception and estimation* by the workers on the production floor, which unfolds the behavioral aspects of such interaction, as underlined in our proposed framework.

Finally, this study explicitly highlights the role of manufacturing flexibility in reshaping the development of different organizational routines in operations management, addressing the recent call to incorporate a more detailed understanding of behavioral elements in the field (Gino and Pisano, 2008; Pagell et al., 2015), in line with other seminal works in the organizational and innovation literature (e.g., Feldman and Pentland, 2003; Rerup and Feldman, 2011). It provides evidence that flexible manufacturing machines have a critical influence on the generation and adoption of new routines over time (Felin et al., 2012), and that varying degrees of manufacturing flexibility influence this generation of routines, as well as individuals' perceptions about the use and the potential of said machines. Our study broadens the understanding of cognitive factors related to space and time in the production process as the result of the interaction between individuals and machines. Our conceptual framework is a first attempt to identify the relationships between manufacturing flexibility and under-investigated behavioral elements. It also includes the digitalization element as moderating factor, thus providing a refined understanding of these relationships to pave the road for future studies in the field.

Our contributions highlight the importance of investigating the impact of digital manufacturing machines in the production process through different theoretical lenses rather than solely using an engineering approach, which is common in the operations management literature. Scholars have shown that digital technologies foster outcomes such as innovation and organizational learning (Colarelli O'Connor, 2008; Hopp et al., 2018; Michael and Palandjian, 2004; Rindfleisch et al., 2017; Svahn et al., 2017), which highlight the need to look at the digitalization phenomenon from different angles. Our study provides such contributions at the intersection between the innovation and operations management literatures, illustrating how digital technologies have disruptive impacts on individuals' space and time routines by increasing dedication to the experimentation phase of the manufacturing process and promoting the development of innovation among external partners.

Implications for Practitioners

Our study provides useful implications for practitioners and suggests some guidelines that can be extended beyond motorsport. To date, the application of recent digital manufacturing technologies has been primarily related to (rapid) prototyping, and in production series, to industries that are characterized by high customization but relatively low volumes of production (e.g., health care, biomedical, aerospace, jewelry). As underlined by Holweg (2015), AM technology undoubtedly holds great opportunities for modern manufacturing, yet it is unlikely (at least in the short term) that it will replace traditional manufacturing machines for large-scale productions. Previous studies investigated the application of digital technologies across various sectors and a broad discussion around benefits and contraindications of such technologies have been, to a certain extent, already advanced (Khorram Niaki and Nonino, 2017; Mellor et al., 2014).

Embracing digital manufacturing technologies is not a trivial task. In fact, Holmström et al. (2019) have recently underlined that digitalization within and across firms will continue to stress traditional approaches in managing production and supply chain processes. Despite the perhaps overly enthusiastic tones in the general press and managerial literature, our findings strongly recommend keeping in mind that digital technologies are far from "plug-and-play" solutions. To take full advantage of their potential, their adoption requires a significant adaptation of the use of space and time, and the careful development of new routines. Aside from cost implications, this study also suggests managers reflect on the impact this might have on existing processes and machines within the organization from a behavioral perspective. Specifically, digital technologies shift the attention toward different phases and activities within the production processes, which require a reorganization of workers on the production floor. Beyond evident changes in the machineries layout due to the introduction of more flexible technologies, this study suggests managers focus their attention on the organizational analysis and design of the relationships that individuals not only have with the machines, but also with each other, as they may trigger the emergence of new behavioral patterns and routines.

Hence, our suggestion is that executives need a better understanding of the behavioral patterns that emerge from the reshaping of space- and time-related routines. Given the challenges that companies face in their digital transformation, this deeper understanding cannot be exclusively related to operations, but also has to consider key strategic implications. This is in line with recent trends in other established managerial approaches such as Lean Manufacturing, where increasing recognition is given to "soft" elements (Bortolotti, Boscari, and Danese, 2015). Therefore, this study recommends managers to undertake precise and detailed assessment of the operational context in terms of involved actors (both internal and external) and technologies adopted in the process, and how they changed before and after the adoption of digital manufacturing machines. Using the outcome of these assessments and their related reflections, managers should implement specific actions for monitoring, supporting, and improving these routine changes. In this direction, appropriate training programs are required to help the different actors in the adoption of new digital technologies, making them aware of how technological adoption will affect both "hard" and "soft" elements. Moreover, it is critical to make managers aware of the possible cognitive biases that the adoption of such machines might entail.

Limitations and Avenues for Future Research

Our work presents several limitations and, as all first attempts, it cannot fully resolve all the compelling open questions related to the impact of new technologies in the production process. Yet, such limitations serve as a stepping-stone for future research, and three promising avenues stand out. First, the focus of this article is the impact of machines that have a physical "hardware" component. Still, it is noteworthy that complex software and intangible resources (such as 3D drawings and intellectual property) are at the basis of such manufacturing technologies. For instance, developing new technological solutions (for motorsport in our case) necessarily involves a series of operations that are conducted in virtual spaces—for example, 3D CAD design, wind tunnel testing with scale models, automatic human-aided computer simulations. Machines that support these types of activities often provide opportunities for increasing experimentation, and particularly in the case of AM, they translate the results of virtual experimentation into physical artifacts, which can be further tested in other virtual spaces, fine-tuned, and transformed again into physical artifacts for enhanced, iterative development. Flexible machines, therefore, represent the link between virtual and real-life experimentation, as they translate virtual ideas into physical artifacts. Future studies could try to reconcile the software and hardware facets of such technologies within digital manufacturing to reach a more holistic view of their behavioral implications—in doing this, greater emphasis should be given to digital and physical interfaces.

Second, despite the fact that such machines represent the operating ground for interorganizational partnerships and relationships, within our endeavor it was only possible to scrape the surface of the complex behavioral aspects within inter-organizational, technology-based projects. Recently, Schorsh and colleagues (2017) highlighted the need to develop a stronger understanding of behavioral elements at the inter-organizational level throughout the supply chain. The social dynamics that emerge from the interaction between technology and individuals belonging to different organizations represent a fertile avenue for future research, as the interactions between partners and flexible technologies determines the amount and type of resources and knowledge exchanged, their relational capabilities (Lorenzoni and Lipparini, 1999), and ultimately affect their related outcomes. Further, such mutual adaptation involves innovation searches, hence shaping the way partners develop new solutions and the value of innovation they are able to extract from their partnership. Future studies could more systematically include external firms in the observation of such technological dynamics.

Third, the machines were samples across a variety of different organizations within the same industry. This was done to increase generalizability and confirm that the emerging findings are relatively stable across a variety of different organizations, which hold different roles in the broader value chain. Yet, it is key to acknowledge that differences across firms and industries might exist and there is a possibility that they might influence, to a certain extent, the establishment of new routines in adopting new digital machines. Future studies might leverage multi-industry samples or to leverage inter-organizational variance to explore the impact of firm-specific factors on the routine establishment.

Ultimately, our study adopts a qualitative methodology that is well suited for studies exploring "soft elements" within the behavioral perspective. Still, such research design cannot fully resolve issues of (reverse) causality and endogeneity. This article thus encourages future studies to pursue more precise analyses of effects and feedback loops associated with flexible machinery adoption. The idiosyncrasies of our setting (i.e., high-tech nature, fast production cycles, extensive use of prototyping, long co-development relations, search for extreme performance) are evident and might limit the generalizability of our findings.

To conclude, following recent calls, our study adopted a *behavioral perspective*—a relatively novel and unusual view in operations and manufacturing domains—to inquire into the timely and disruptive phenomenon of digital manufacturing innovation. The identified conceptual framework is by no means exhaustive, but hopefully our broadening endeavor will trigger fruitful conversations and contributions.

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